Tarrodan Re

Presented by Factuarial

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1. Executive Summary

Floods don't just break dams—they break budgets. Their growing frequency, alongside dam failures, threatens both infrastructure and financial stability. Current insurance models rely on either government-backed reserves (e.g., the Netherlands [Sanon, H. 2024], Canada [Canada, P.S. 2025]) or mostly privatized systems (e.g., the United States [Bowman, A. 2014]). Neither approach reliably balances pricing equity and market stability.

This report proposes a hybrid, multi-layered risk transfer model. It spreads flood risk across three groups: direct insurers, regional reinsurers, and the government. Direct insurers compete for individual policies. Regional reinsurers manage high-risk zones and maintain dams. The government provides targeted subsidies and acts as the catastrophic backstop. If this model had been in place over the past 23 years, reserve needs could have dropped from Q335 billion to Q89 billion—a Q246 billion reduction. Savings would come from lower payouts, improved dam maintenance, and greater insurer participation. Fewer dam failures. Fewer disasters. Stronger economies. Safer communities. Sensitivity analysis shows the model boosts both economic and social resilience with near certainty. Key risks include insurer insolvency, reinsurer hesitation, monopolies, and inconsistent inspections. We recommend four safeguards: capital reserve rules, tax incentives for reinsurers, pricing regulations, and standardized inspections. Together, these protect financial stability and long-term success.

2. Objectives

This program aims to stabilize Tarrodan's finance and infrastructure through two core objectives:

1. Move from a full government model to a layered risk model to reduce fiscal burden.
2. Incentivize maintenance and infrastructure upgrades to reduce flood frequency.

Program success will be measured by these two metrics:

- Reduced government flood-related expenditures, through lower claim payouts, improved dam maintenance, and increased private-sector participation.
  - Measured by budget impact, comparing disaster assistance and insurance reserve costs before and after implementation
- Decreased flood incidence, via proactive infrastructure maintenance.
  - Measured by tracking changes in flood frequency over time

Implementation is divided into three phases:

- **Setup Phase (6–12 months):** Establish regulatory frameworks, onboard direct insurers and reinsurers, and implement data-driven risk assessment tools.
- **Delivery Phase (Years 1–3):** Deploy subsidies, standardize inspection protocols, and incentivize preventative maintenance through structured insurance pricing.
- **Evaluation Phase (Ongoing, every 6–12 months):** Monitor spending reductions, track flood occurrences, and refine risk-sharing mechanisms based on actuarial analysis.

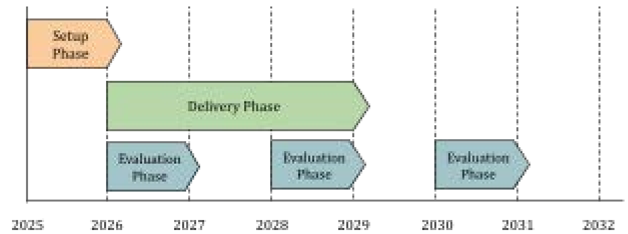


Figure 1: Implementation Timeframe for Overall Program

Initial budgetary improvements may emerge within a few years. Full flood prevention benefits will take 5–10 years to materialize. Continuous monitoring and iterative improvements will be essential for lasting resilience.

3. Program Design

3.1. Evaluation of Insurance Models & Proposal

This section evaluates two opposing flood insurance models: a fully government-backed national program and a fully privatized market. Neither extreme is viable for Tarrodan, given the financial and structural demands of effective flood risk management.

A fully government-backed model ensures universal coverage, affordability, and coordinated national mitigation efforts (Thistlethwaite & Henstra, 2024). Subsidies keep high-risk homeowners insured, while state investment supports large-scale infrastructure projects. However, this model has critical weaknesses. Disaster relief costs are soaring, straining fiscal sustainability. Governments often lack incentives for regular infrastructure upkeep, leading to poorly maintained dams and potential insurer bailouts (Texas Commission on Environmental Quality, 2006). In Canada, post-disaster relief is increasingly unsustainable. In the Netherlands, despite full state control, doubts remain about the sufficiency of public funding for long-term infrastructure maintenance (Glas, 2022). As Ontario's flood risk report (2024) notes, governments may lack both the expertise and capacity for effective mitigation.

A fully privatized market, by contrast, introduces risk-based pricing, ensuring low-risk homeowners don't subsidize high-risk ones (Bossio & Ness, 2024). Competition promotes efficiency—insurers refine risk models, incentivize prevention, and control costs. Yet privatization often limits affordability and access (Moyana, 2025). In Florida, private insurers frequently deny coverage or set unaffordable premiums in flood-prone areas, leaving many reliant on last-resort state programs like Citizens Property Insurance (Smith, 2024). While fiscally stable, privatization fails to protect vulnerable populations against adverse selection.

Neither system works in isolation. Terrodan needs a hybrid model. Our proposal blends the strengths of both systems while mitigating their flaws. The following sections detail its structure and phased implementation.

3.2. Role of Direct Insurers – Liquidity & Competitive Pricing

A resilient direct insurance market is key to maintaining liquidity and fair, risk-based pricing in flood coverage (IAIS, 2024). Insurers must balance accurate pricing with affordability. But without government support, market forces alone can't ensure competition or access. Direct insurers face two main challenges: limited capital and high entry costs (OECD, 2016).

First, many lack the reserves to handle extreme, right-skewed losses (Stephenson, 2023). Flood claims are rare but severe, threatening solvency (Prost, 2024). Small markups over expected losses leave insurers exposed. One major event can wipe them out. To stay afloat, they raise premiums. Higher prices drive down participation. Liquidity shrinks. Access fades. A vicious cycle begins. Second, high entry costs block new competitors (Hayes, 2024). Flood insurance needs strong finances and advanced modeling tools. Software like GGY Axis is essential—but expensive (Hedegaard, 2018). Small insurers can't afford it. Premiums rise. Consumer choice shrinks. To fix these barriers, we propose five targeted interventions:

1. **Reinsurance Support for Extreme, Right-Skewed Losses** *(See Appendix A for visual)*
   To ease financial strain on direct insurers, the government will encourage greater reinsurance participation. Claims above the 80th percentile will be ceded to reinsurers, protecting insurers from catastrophic losses and promoting premium stability.
2. **Subsidized Access to Predictive Modeling Software**
   High software costs are a major barrier for small insurers. To level the playing field, the government will subsidize access to tools like GGY Axis. This increases competition, improves pricing accuracy, and enhances consumer access.
3. **Grants and Financial Support for InsurTech Startups**
   Innovation is crucial for a competitive and efficient market. Government grants will support InsurTech firms developing AI-powered risk models and advanced underwriting systems. These tools reduce operational costs and improve affordability.
4. **Open Government Data for Risk Assessment**
   Regulated insurers will gain free access to key datasets—including weather forecasts, flood histories, and infrastructure assessments. This reduces data collection costs, promotes fair competition between new and established players, and ultimately drives down premiums.
5. **Compulsory Insurance Bundling**
   As outlined in Section 3.4, flood insurance will be bundled with standard property insurance. Bundling increases participation, simplifies the purchase process, reduces consumer resistance, spreads risk more broadly, and boosts market stability.

3.3. Role of Reinsurers – Risk Absorption & Infrastructure Stewardship

Reinsurers do more than absorb catastrophic losses—they sustain the insurance ecosystem by pooling capital and enabling competition among smaller firms. In our model, reinsurers evolve from passive risk carriers into proactive infrastructure stewards, actively supporting dam maintenance and mitigation efforts.

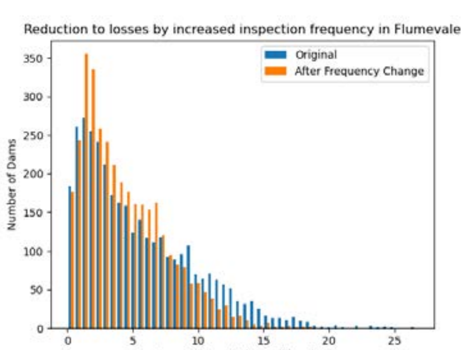
The Need for Reinsurers to Lead Dam Maintenance

Tarrodan's dam inspection system is severely inadequate. Cross-regional analysis reveals that over 48% of records lack inspection dates, and more than 40% omit inspection frequency data. The result: inconsistent, unstandardized inspections that heighten systemic flood risk. Actuarial studies confirm an inverse correlation between inspection frequency and flood losses—more inspections mean fewer catastrophic failures. While government-led intervention seems intuitive, it often falls short. Public agencies typically lack the technical capacity to design optimal inspection schedules and frequently treat infrastructure upkeep as a financial burden (T.K., 2024). Maintenance funding is inconsistent and vulnerable to political shifts, leading to dangerous delays in critical repairs.

Why Reinsurers Are a Better Choice

- **Stronger Financial Incentives & Risk Expertise –** With exposure to catastrophic losses, reinsurers are financially motivated to invest in prevention. Their actuarial tools support data-driven inspections and maintenance.
- **Long-Term Stability & Efficiency –** Reinsurers operate beyond political cycles, applying consistent strategies to infrastructure risk over time.
- **Catalyst for Private Investment –** Their involvement can draw private capital into flood mitigation, advancing engineering solutions and predictive technologies, while reducing reliance on public funds (Jordan-Tank, 2017).

Incentive Structure for Enhanced Maintenance Efforts



To formalize reinsurer engagement, we introduce a performance-based incentive system tied to inspection frequency. Initially, the government's reimbursement threshold is set at the 95th percentile, covering catastrophic losses above \$200–\$350 billion, depending on the region. However, exploratory data analysis shows

Figure 2: Increasing Minimum Inspection Frequency to 5 Showcases a Significant Decrease in Expected Losses

a clear inverse relationship between inspection frequency and loss magnitude (see Appendix A). To encourage proactive action, the threshold adjusts dynamically. For example, increasing inspections from two to eight per cycle reduces the reimbursement threshold from $350 billion to $275 billion. This creates a financial incentive for reinsurers to fund maintenance oversight and reduce catastrophic exposure.

Structured Approach for Implementation *(refer to Appendix B for detailed calculations)*

1. **Fixed Reserve –** The reserve remains constant, adjusted for inflation, for fiscal planning.
2. **Reserve Calculation –** Based on a normal distribution, reserves = Expected Loss + 3σ, ensuring 99.7% coverage under the Law of Large Numbers (Ross, 2024).
3. **Initial Thresholds –** Attachment points begin at the 95th percentile of loss distribution.
4. **Machine Learning Integration –** A dynamic model, powered by Google's YDF (see Appendix C), adjusts thresholds based on updated inspection data. This ensures precise alignment between inspection frequency and fiscal exposure.

**Note: Inspection frequency is capped at 9, details are available in the sensitivity analysis.*

3.4. Role of the Government – Subsidies, Retrocession, and Regulatory Oversight

Beyond subsidies and retrocession (Sections 3.2 and 3.3), the government plays key roles in regulation, standard enforcement, and managing extreme-risk scenarios—the "one percent problem" (Thistlethwaite & Henstra, 2024).

First, regulatory oversight ensures direct insurers and reinsurers act ethically, transparently, and efficiently. By consulting experts, the government sets strict licensing standards. Only insurers that meet them receive subsidies and financial support. Regulations also mandate clear guidelines for dam inspections and maintenance. This stops reinsurers from inflating inspection frequencies or cutting quality for profit. Without oversight, insurers may end up funding poorly maintained infrastructure, shifting costs unfairly to them. Strong regulation prevents this. It maintains integrity, accountability, and resilience in the system. Second, the "one percent problem" needs targeted action. Properties in the top one percent can cause 40% of expected losses (Thistlethwaite, J., 2025). These homes—considered uninsurable—will be excluded from compulsory insurance. Instead, owners get a one-time disaster payment under a "one and done" policy. This can be used to rebuild or relocate. The goal is to encourage moves to safer areas and reduce high-risk housing over time.

This targeted exclusion also mitigates adverse selection. By removing the costliest properties from the risk pool, premiums for the remaining 99 percent become both lower and more equitable. A case study shows that the average housing price for top one percent properties is significantly higher than the national average. This raises a serious social equity concern: people might be angry knowing that they pay the insurance for some rich guy's mansion near the tropical beach. Excluding these properties from the compulsory scheme avoids this issue and strengthens public support for the program. To further prevent adverse selection, flood insurance is bundled with standard property insurance. This ensures wide participation and stable pricing. Premiums vary by region to reflect local flood risk. Homeowners pay their fair share—no more, no less. At the same time, the government promotes self-insurance for the highest-risk properties. These owners are encouraged to invest in flood protection or relocate. This aligns with broader buyout programs to reduce vulnerable housing. A "sunset clause" (Thistlethwaite, J., & Henstra, D., 2024), based on the UK model, supports long-term risk reduction. Regions have ten years to upgrade flood infrastructure like dams and levees. If benchmarks aren't met, insurers may withdraw coverage. This clause empowers citizens to demand timely upgrades and supports stronger negotiations with reinsurers.

Taken together, these strategies integrate the government's regulatory and financial roles to promote sustainability, market equity, and risk mitigation—while empowering citizens and preserving the long-term viability of the national flood insurance landscape.

3.5. Evaluation Time Frame

The evaluation timeline establishes a structured framework for monitoring and refining the proposed hybrid insurance model. This systematic approach ensures ongoing assessments of financial sustainability, market competitiveness, and infrastructure resilience. Defined evaluation intervals for key stakeholders—direct insurers, reinsurers, and government regulators—facilitate continuous oversight and data-driven policy adjustments.

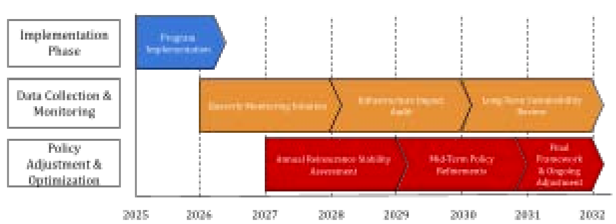


Figure 3: Evaluation Timeframe for Overall Program

4. Financial Results

4.1. Government Inflows: Revenue Sources

The financial structure of the hybrid program relies on a well-balanced system of inflows and outflows, designed to ensure long-term viability. On the inflow side, the government derives revenue from two key sources. First, region-specific tax contributions are levied across Lumaria at differentiated rates based on economic capacity and flood exposure: 0.10% of GDP in

Flumevale, 0.80% in Lyndrassia, and 0.15% in Navaldia. This tax structure ensures equitable contribution across regions, generating an estimated $44,096 QM over a ten-year period while aligning revenue with risk and regional output. Second, licensing fees collected from participating private insurers and reinsurers support both regulatory oversight and infrastructure development. As the program scales, these fees are expected to rise proportionally with the number of participating entities, further reinforcing the government's capacity to sustain and manage national flood risk.

4.2. Government Outflows: Expenditures

On the expenditure side, the government covers catastrophic losses that exceed the private sector's capacity. The largest cost comes from claim payouts during extreme flood events. Models project average annual payouts of $3,859 QM in Flumevale, $3,893 QM in Lyndrassia, and $4,911 QM in Navaldia, depending on flood severity and frequency. These payments are key to keeping insurers in the program and protecting policyholders from major financial loss. The government also provides $50 QM annually in targeted subsidies. These go to smaller insurers—especially along the GGY axis—who face higher risk and financial strain during extreme weather. The subsidies help them stay solvent, preserve market competition, and prevent consolidation that could drive up premiums and limit consumer choice. The program also incurs approximately $50 QM annually in operational expenditures. These funds support regulatory oversight, continuous data collection, and the deployment of AI-driven risk modeling systems. By refining flood risk assessments in real time, these tools improve forecasting accuracy, enhance resource allocation, and contribute to loss mitigation.

4.3. Long-Term Fiscal Sustainability

Fiscal sustainability is a core pillar of the program's design. Government reserves are projected to remain relatively stable, supported by low variability in data trends and steady reserve growth. Subsidies are structured with built-in flexibility, allowing for real-time adjustments based on evolving flood risk patterns and new climate data. This dynamic approach ensures continued responsiveness to external shocks, such as climate change, rather than relying on static funding models. Reserves are expected to grow at an annual rate of 4.5%, gradually expanding the government's capacity to absorb catastrophic losses without overextending public finances. These reserves serve as a financial buffer, enabling the state to fulfill its role as insurer of last resort while maintaining long-term fiscal discipline. To ensure affordability and equity, residents of Flumevale contribute 0.10% of their average salary, while those in Lyndrassia and Navaldia contribute 0.80% and 0.15%, respectively. All contribution rates remain well below the 1.8% threshold which is the upper limit of affordability for insurance (Thistlethwaite & Henstra, 2024). This structure ensures accessibility while maintaining proportionality across regions.

4.4. Budget vs Current Contributions

To assess the fiscal impact of the hybrid model, we compare its reserve requirement to a counterfactual scenario in which the government assumes full responsibility for flood risk. Under a government-only model, maintaining sufficient reserves to cover all claims would require $27907 to $32365 QM per region. This estimate accounts for direct payouts, operational costs, and preventative measures, with no risk transfer to insurers or reinsurers. In contrast, the hybrid model leverages private capital, reducing the government's reserve requirement to $4911 to 3859 QM per region over the same period. The resulting more than $20000 QM reduction per region significantly alleviates fiscal pressure, freeing resources for other public priorities. Beyond budgetary relief, this approach enhances economic stability by unlocking capital that would otherwise remain tied up in reserves, fostering economic activity.

5. Key Assumptions

Metric	Description	Rationale
Current Government Reserves	$88,501 QM required under a government-only model to cover all claims without private sector support.	Based on stable historical growth and economic forecasts, ensuring the government can fulfill its insurer-of-last-resort role.
Expected Loss Distribution	Losses follow a Normal distribution, validated by QQ plot to account for skew.	Catastrophic flood losses are best modeled with a Normal distribution, where a few events drive most losses *(see Appendix A)*.
Average Maintenance cost per dam	The estimated rehabilitation cost per dam is 0.81 M (USD) = 0.77QM. (ASDSO, 2016)	This is based on data from the Association of State Dam Safety Officials, which provides region-specific estimates on dam repair and maintenance expenses.

6. Risk and Risk Mitigation Considerations

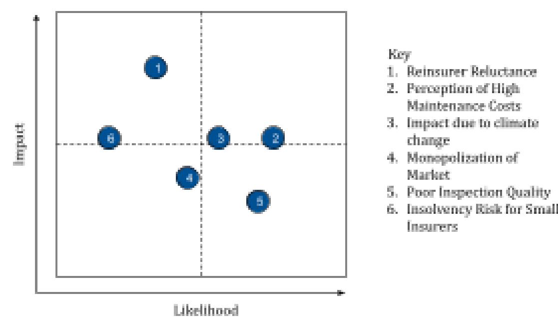
6.1. Main Risks

The main risks facing the flood insurance sector include **reinsurer reluctance in high-risk zones**, the **perception of high maintenance costs**, and the **growing impact of climate change.** Reinsurers may withdraw from high-risk flood areas, reducing market capacity and driving up premiums. To mitigate this, governments can introduce tax incentives and direct subsidies, creating a cost-sharing model where a percentage of reinsurers' expenses in such zones is covered. Additionally, reinsurers may hesitate to invest in preventive maintenance due to perceived high costs, increasing the likelihood of catastrophic claims. This can be addressed by promoting data-driven evidence of long-term cost savings and claim reductions through preventive action. Lastly, climate change introduces unpredictable weather patterns that increase dam vulnerability and complicate flood risk forecasting. Mitigation strategies include reinforcing dam and flood defense infrastructure and regularly updating flood risk models with the latest climate data to ensure accurate risk assessment and premium pricing.

6.2. Risk Matrix

The risk matrix highlights that most primary risks have a moderate likelihood of occurrence but a high potential impact on the program's performance. These risks pose significant threats to financial stability and operational continuity. To counteract this, the mitigation strategies outlined in Section 6.1 and appendix E have been rigorously implemented. These measures ensure the hybrid insurance program remains viable and resilient against potential disruptions.

Figure 4: Risk Matrix



6.3. Sensitivity

Sensitivity testing on inspection frequency reveals that the optimal range lies between 0 and 9 inspections per cycle, with the most significant reductions in payouts occurring around 6 inspections. Beyond nine, additional inspections yield minimal improvements in payout reduction, indicating diminishing returns. This 0–9 range effectively balances risk mitigation—by reducing dam failure likelihood—with resource efficiency, while maintaining stable government reserves. Assessment level sensitivity shows a clear relationship between structural condition and expected payouts. As assessment levels decline from "Satisfactory" to "Poor," expected payouts increase significantly: by 32.2% in Flumevale, 20.3% in Lyndrassia, and 14.1% in Navaldia. Flumevale is the most sensitive to poor assessment outcomes, underscoring the need for improved maintenance to reduce losses. Ensuring that all structures meet at least a "Fair" assessment level is critical to minimizing regional financial exposure.

7. Data and Data Limitations

7.1 Data Sources

This analysis draws on four key sources.

1. The Reimbursement for Damages Act (Ministerie van Infrastructuur en Waterstaat, 2023) the Netherlands' criteria for disaster-related damage reimbursement. It provides insight into public policy for distributing financial aid after disasters.
2. 2. The Cost of Rehabilitating Our Nation's Dams report (ASDSO, 2016) offers an updated comprehensive assessment of dam rehabilitation expenses across U.S. regions.
3. 3. Public Safety Canada (2025) details two major Canadian disaster response programs: the Disaster Financial Assistance Arrangements (DFAA) and the Canada Flood Insurance

Program (CFIP). These programs operate as federal cost-sharing models,and serve as a reference for assigning financial responsibilities in disaster recovery efforts.

4. 4. Wang (2021) presents a machine learning-based data cleaning method using the K-Nearest Neighbor (KNN) classifier. The study introduces classification ability ranking to manage missing data, improving the quality of datasets in predictive risk modeling.

<u>7.2. Data Limitations</u>

1. Dam-related metrics are incomplete, with significant gaps across key categories—most notably, 51% of entries lack data on the "Assessment Date." Thisigh level of missing information may distort loss projections and require further validation.
2. The absence of precedent hybrid insurance programs means there are no existing benchmarks for estimating maintenance costs or reserve structures. As a result, the model relies on assumptions about operational costs, which may affect precision.
3. Limited direct data available on dam maintenance costs, introducing uncertainty into operational expense forecasts and expected cost savings.
4. Finally, the lack of information on current government-held flood insurance reserves and active policy structures necessitated assumptions in modeling reserve requirements and potential fiscal benefits. These data gaps introduce risks of inaccuracy in evaluating the proposed policy's long-term impact.

8. Conclusion and Next Steps

By implementing our approach, we anticipate a substantial influx of dam-related data as inspection and maintenance practices improve. This enriched data environment will allow for continuous refinement of our predictive models, enabling the setting of more precise thresholds and optimized premium pricing. Over time, Terrodan can reduce the government's flood mitigation budget by 40.6% while lowering the total number of dam failures. The result: enhanced public safety and stronger social outcomes.

Looking ahead, one promising extension involves the integration of advanced machine learning techniques to assess individualized property risk premiums. This would require collecting granular property-level data—such as elevation relative to flood plains, building materials, foundation type, and other structural characteristics—and feeding it into high-precision predictive models. Much like in the real estate market, the resulting premium values would be made publicly available. This transparency empowers homeowners with clear, data-driven insights into their flood risk. It also shifts market dynamics. Insurers, now facing more informed customers, would be incentivized to offer more competitive pricing and better coverage terms. Initially, this effort could begin with detailed case studies in high-risk regions to identify key predictive features. Over time, it would scale to a fully integrated, nationwide pricing framework—one that aligns actuarial fairness with technological innovation.

9. Appendix A – Exploratory Data Analysis

During exploratory data analysis, we applied K-Nearest Neighbors (KNN) with cross-validation to determine the optimal k-value for imputing missing quantitative data. We introduced "total loss" and "expected loss" variables to enhance interpretability and removed "last inspection date" due to over 90% missing values. Categorical gaps were addressed by introducing a "missing" level.

Additionally, univariate and bivariate analysis revealed key data patterns:

- **Layered Risk Structure**: The right-skewed distribution of total loss aligns with the proposed tiered risk allocation.

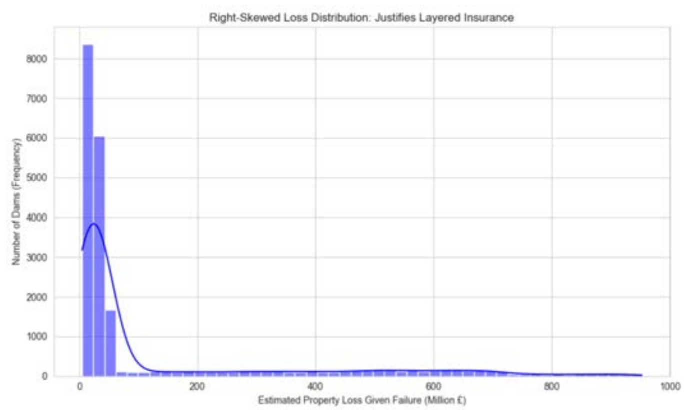


Figure 5: Loss distribution between Number of Dams and Expected Loss

- **Dam Age & Failure Risk**: There is no clear trend between damage and failure probability or total loss.

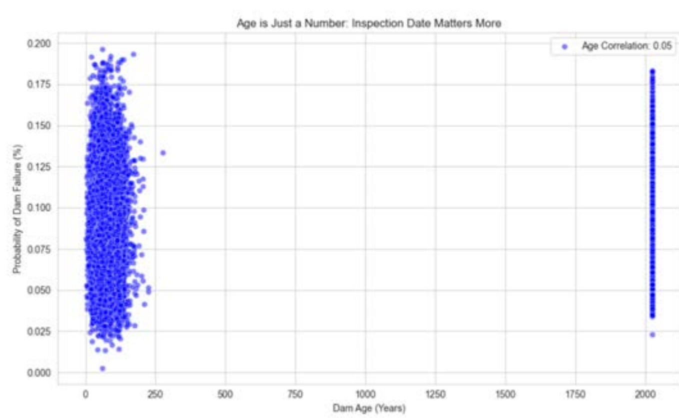


Figure 6: Correlation between Age and probability of failure

- **Inspection Frequency & Failure Probability**: A strong correlation suggests that government-backed risk adjustments based on inspection history could be justified.

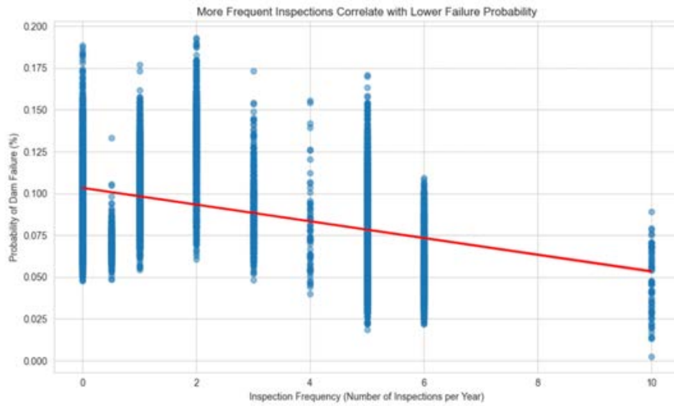


Figure 7: Relationship between Inspections Frequency and the Probability of Failure

- **Regional Risk Segmentation**: Certain regions (e.g., Flumevable) have relatively few dams but high expected losses, reinforcing the need for government intervention.

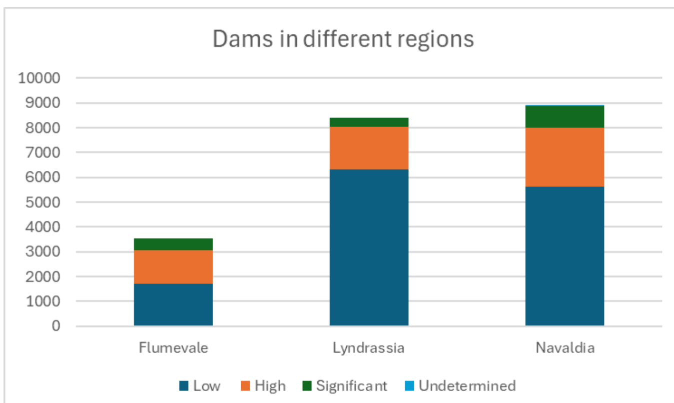


Figure 8: Number of Dams with their Hazard Level in Specific Regions

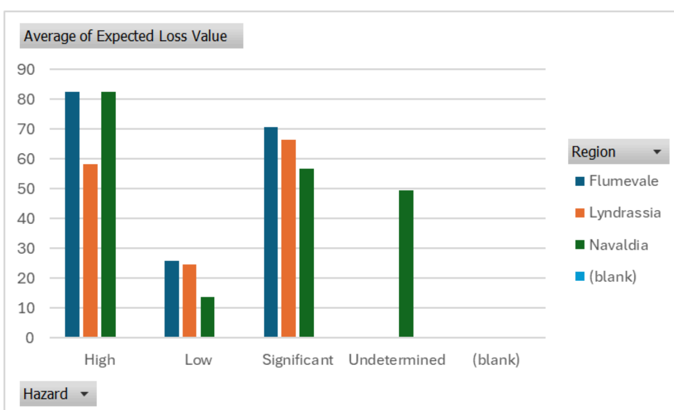


Figure 9: Expected Loss according to Different Hazard Level in Different Regions

- **Urban Exposure & Premium Subsidization**: Dams near cities pose higher financial risks, suggesting that government subsidies may be necessary to maintain insurability.

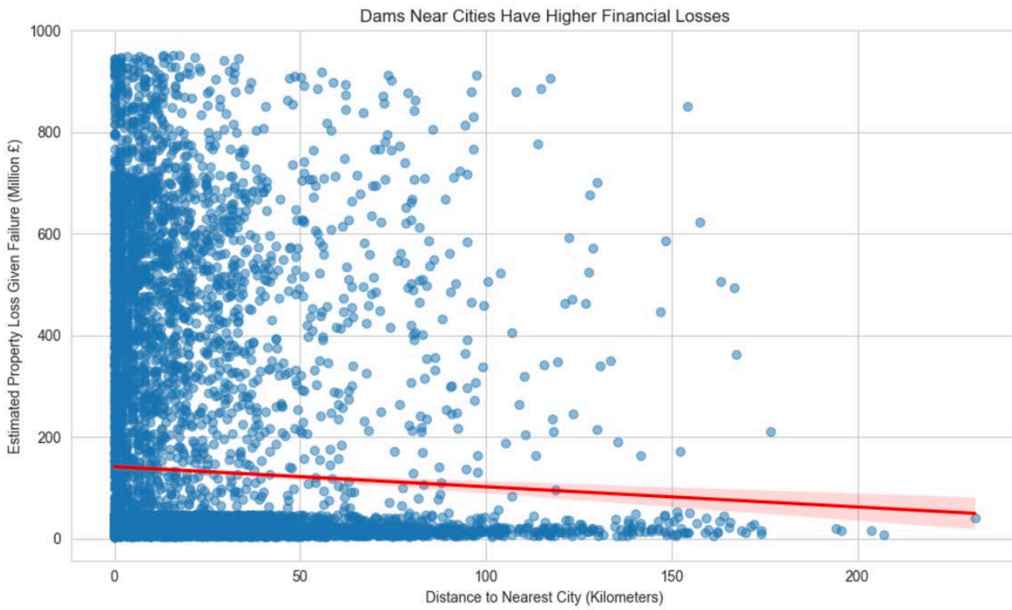


Figure 10: Relationship between Distance with City and the Total Financial Loss

- **Market Stability Risks**: The highest-risk dams (top 10% of projected failures) contribute disproportionately to expected financial losses, highlighting the potential need for government support.

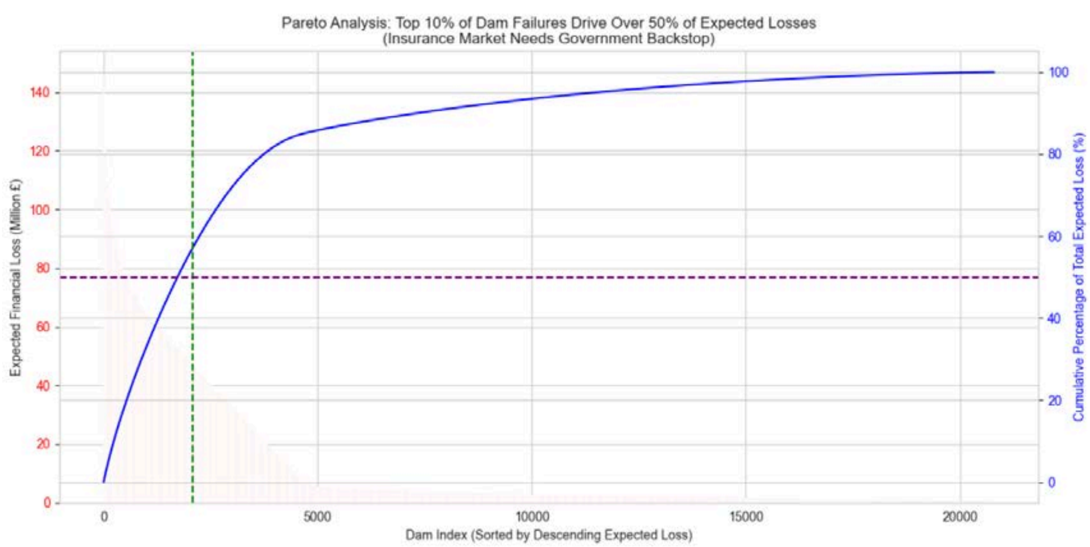


Figure 11: Pareto-like Graph: Cumulative Total Loss

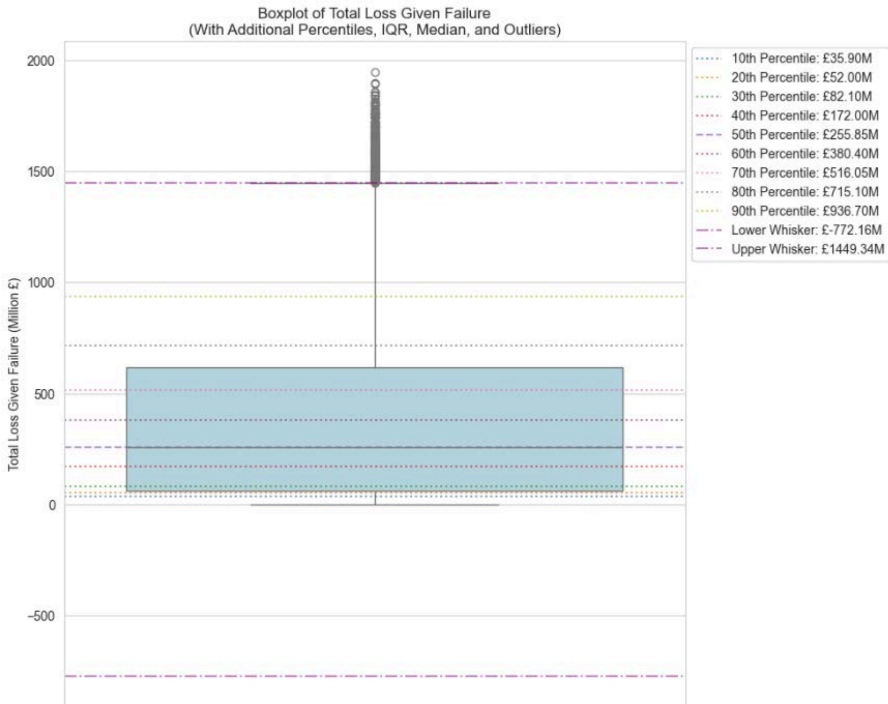


Figure 12: BoxPlot for Expected Loss

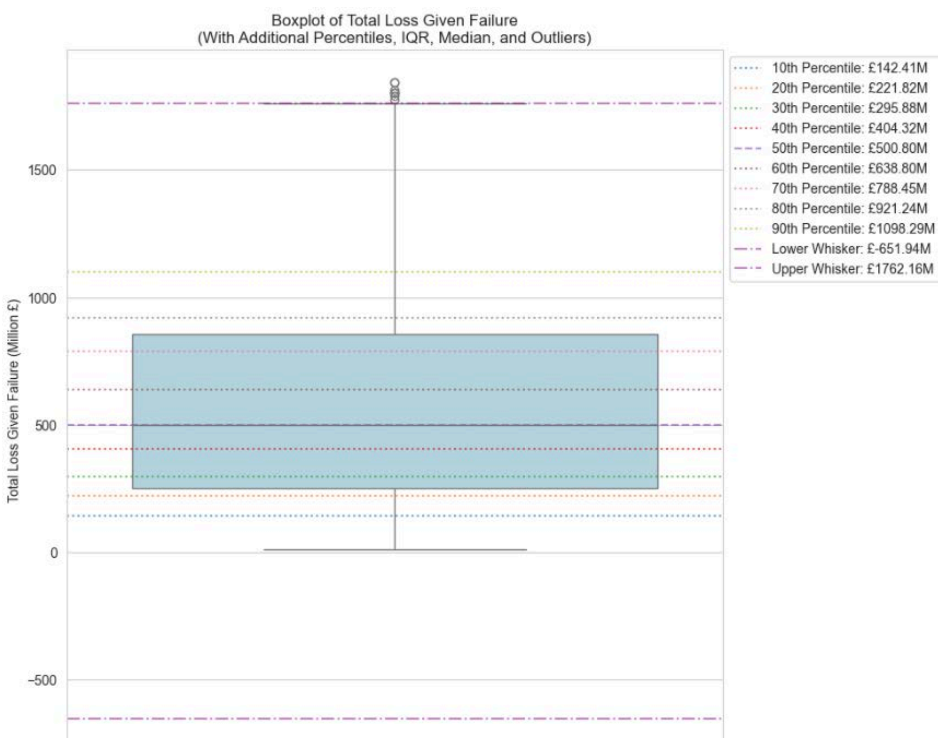


Figure 13: BoxPlot for Expected Loss for Flumevale

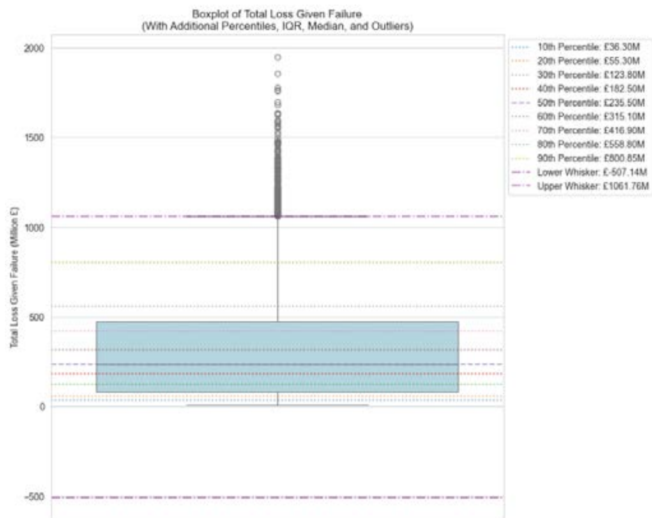


Figure 14: BoxPlot for Expected Loss for Lyndrassia

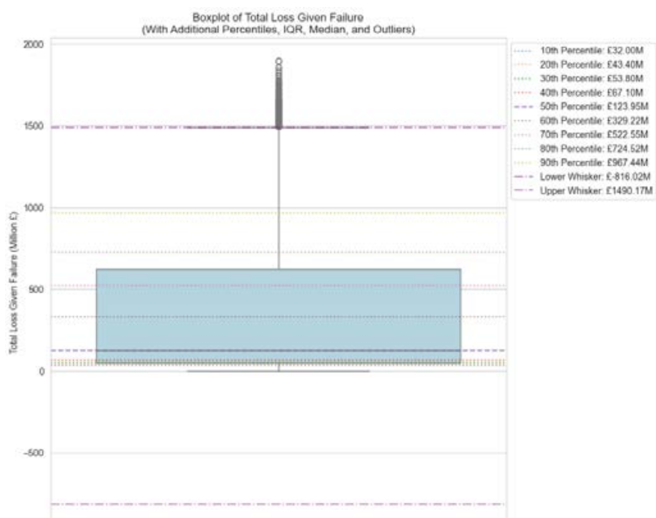


Figure 15: BoxPlot for Expected Loss for Navaldia

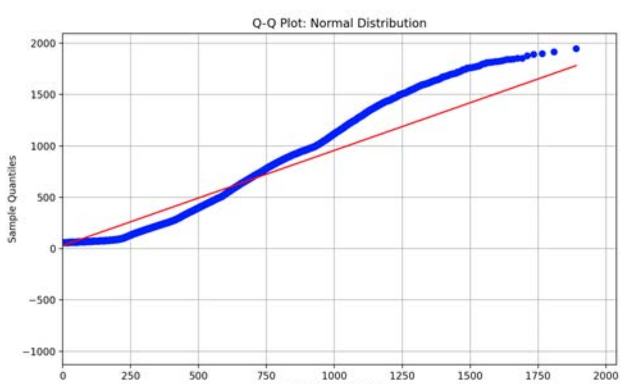


Figure 16: Normal Q-Q Plot for Expected Total Loss

10. Appendix B – Technical Explanation of Government Reserve and Threshold Adjustments

Our system operates through a structured, actuarially sound framework, as shown below:

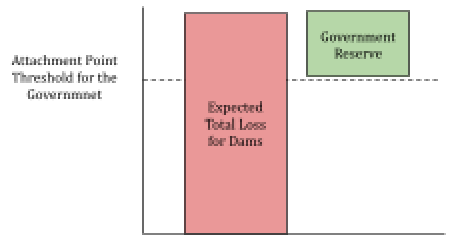


Figure 17: Initial Reserve Determination

- Expected Total Loss: Modeled average loss from dam failure and flooding.
- Attachment Point Threshold: The loss level (e.g., $350B → $275B) at which government reimbursement begins.
- Government Reserve: Calculated as Expected Loss + 3 standard deviations, ensuring a 99.7% confidence level under extreme loss scenarios (CPMI-IOSCO, 2024).

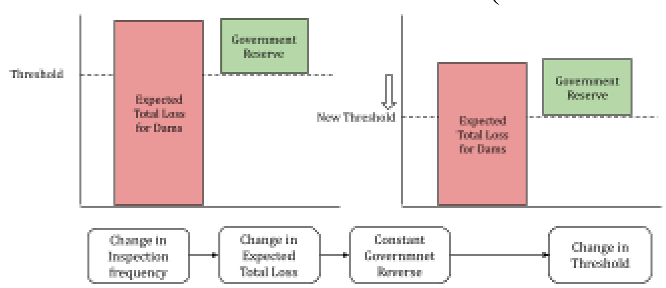


Figure 18: Adjusting Threshold with Inspection Frequency

- Impact of Inspections: More inspections lower expected loss by reducing failure likelihood and severity.
- Threshold Recalibration: With a constant reserve, the attachment point adjusts to reflect reduced risk.
- Incentive Alignment: This structure rewards reinsurers for proactive inspections while preserving fiscal discipline.

11. Appendix C – Code for YDF Machine Learning Model for inspection frequency

A link to the remaining code base can be found here:
https://github.com/kevinj637/SOA_research_comp2025

Machine_learning.py code:

```
#libraries we used to create out program
import pandas as pd
import numpy as np
import ydf
import matplotlib.pyplot as plot
import gov_expenditure
import scipy.stats

#this function returns the new government threshold based on their percentile of involvement and minimum frequency
def expected_losses_given_min_frequency(file : str, frequency : int, initial_percentile: float, make_graph : bool, verbose : bool) -> tuple:
    #decode the file
    df = pd.read_csv(file)
    train_df = df.copy(True)
    #The columns were dropped for the following reasons:
    #ID: Independent from data
    #Years Modified: Insufficient data
    #Assessment date: insufficient data
    # loss given failure (all varieties): independent from dam failure probability rate
    # hazard: independent from dam failure probability rate
    train_df = train_df.drop(columns=["ID", "Years Modified", "Assessment Date", "Assessment Date","Loss given failure - prop (Qm)","Loss given failure - liab (Qm)", "Loss given failure - BI (Qm)", "Total Loss Given Failure", "Expected Loss Value", "Hazard"])
    test_df = train_df.copy(True)

    # adjust all frequencies to be at least minimum frequency
    for i in range(test_df.index.size):
        if (test_df.loc[i, "Inspection Frequency"] < frequency):
            test_df.loc[i, "Inspection Frequency"] = frequency
```

```
    ydf.verbose(0)

    #run machine model
    model = ydf.GradientBoostedTreesLearner(label="Probability of Failure",
task=ydf.Task.REGRESSION,).train(train_df)
    ydf_prediction = model.predict(test_df)

    for i in range(test_df.index.size):
        test_df.loc[i, "Probability of Failure"] = ydf_prediction[i]

    #input machine trained-information
    new_df = df.copy(True)
    new_df = new_df.replace(new_df["Probability of Failure"], pd.Series(ydf_prediction))
    for i in range(new_df.index.size):
        new_df.loc[i, "Expected Loss Value"] = test_df.loc[i, "Probability of Failure"] *
new_df.loc[i, "Total Loss Given Failure"]
    new_df.to_csv(f"machine_learning_frequency_adjusted_{df.loc[0, "Region"]}.csv", index =
False)

    #make graph
    if make_graph:
        compare_new = new_df["Expected Loss Value"].div(10).to_numpy()
        compare_old = df["Expected Loss Value"].div(10).to_numpy()
        plot.hist([compare_old, compare_new], bins=50,label=["Original", "After Frequency
Change"])
        plot.xlabel("Expected Loss Value, millions(£Q)")
        plot.ylabel("Number of Dams")
        plot.title(f"Reduction to losses by increased inspection frequency in {df.loc[0, "Region"]}")
        plot.legend()
        plot.savefig(f"frequency_adjusted_expected_loss_{frequency}_{df.loc[0,
"Region"]}_histogram.png")
        plot.clf()

    #do computations to obtain our government threshold and reserve
```

```
    new_data =
gov_expenditure.yearly_loss_percentile(f"machine_learning_frequency_adjusted_{df.loc[0,
"Region"]}.csv", 0, 100, verbose)
    old_data = gov_expenditure.yearly_loss_percentile(file, 0, 100, verbose)
    gov_threshold = scipy.stats.norm.ppf(initial_percentile/100) * old_data[2] + old_data[1] #one
standard deviation, covers 95% to 99.7% of all cases
    gov_reserve = scipy.stats.norm.ppf(0.997) * old_data[2] + old_data[1] - gov_threshold
    new__gov_detachment_point = scipy.stats.norm.ppf(0.997) * new_data[2] + new_data[1] #the
amount of money for 99.7% of all cases
    new_gov_threshold = new__gov_detachment_point - gov_reserve
    new_percentile = scipy.stats.norm.cdf(new_gov_threshold, new_data[1], new_data[2])
    if verbose:
        print("Based on the original data, the threshold should be:", gov_threshold, "and the reserve
is", gov_reserve)
        print(f"The expected value of the new data is {new_data[1]} with standard deviation
{new_data[2]}.")
        print(f"This means the government detachment point is {new__gov_detachment_point} and
the detachment point is {new_gov_threshold}.")
        print(f"The insurance companies will expect to pay {new_data[1]} instead of {old_data[1]}.
This represents a decreased payout of {new_data[1] - old_data[1]}")
        print(f"The government threshold will also shift by {new_gov_threshold - gov_threshold}")
        print(f"This is the {new_percentile * 100} percentile.")

    #return important information
    ans = {f"Threshold percent {df.loc[0,"Region"]}" : new_percentile}
    ans.update({f"Original Threshold {df.loc[0,"Region"]}": gov_threshold})
    ans.update({f"New Threshold {df.loc[0,"Region"]}" : new_gov_threshold})
    ans.update({f"Change in Threshold {df.loc[0,"Region"]}" : new_gov_threshold -
gov_threshold})
    ans.update({f"Original Expected Payout {df.loc[0,"Region"]}" : old_data[1]})
    ans.update({f"New Expected Payout {df.loc[0,"Region"]}" : new_data[1]})
    ans.update({f"Change in Payout {df.loc[0,"Region"]}" : new_data[1] - old_data[1]})
    return ans
```

Gov_expenditure.py code, calculates the expected loss and government reserves of a region:

```
def yearly_loss_percentile(file : str, lower_percentile : int, upper_percentile : int, verbose : bool)
-> (tuple):
    df = pd.read_csv(f"{file}")
    df.sort_values("Expected Loss Value", axis= 0, ascending=True, inplace=True)
    lower_bound = int(df.index.size * lower_percentile / 100)
    upper_bound = int(df.index.size * upper_percentile / 100)
    df_analyze = df.iloc[lower_bound:upper_bound]
    expected_value = df_analyze.get(["Expected Loss Value"]).sum()
    total_loss_avg = df_analyze.get(["Total Loss Given Failure"]).sum()
    df_analyze.to_csv(f"outlier_{file}")
    cumulative_variance = 0
    if verbose:
        print(df_analyze.columns.get_loc("Total Loss Given Failure"))
    for i in range(df_analyze.index.size):
        second_moment = df_analyze.iloc[i, 18] * df_analyze.iloc[i, 22] * df_analyze.iloc[i, 22]
        variance = second_moment - df_analyze.iloc[i, 23] * df_analyze.iloc[i, 23]
        cumulative_variance = variance + cumulative_variance
    expected_value = expected_value / 10
    cumulative_variance = cumulative_variance / 10
    standard_deviation = math.sqrt(cumulative_variance)
    if verbose:
        print(f"""Region: {df.iloc[3,1]}\nAverage Loss Given Failure:
{total_loss_avg.values[0]}\nExpected Value: {expected_value.values[0]}\nStandard Deviation:
{standard_deviation}\nVariance: {cumulative_variance}\nNumber of Dams:
{df_analyze.index.size}\nExpected Reserves: {z_value(standard_deviation,
expected_value)}\n\n""")
    return total_loss_avg.values[0], expected_value.values[0], standard_deviation,
cumulative_variance, df_analyze.index.size
```

Specific Performance of the YDF machine-learning model:

Task: REGRESSION
Loss (SQUARED_ERROR): 0.0138698
RMSE: 0.11777

Specific characteristics regarding inputs used for the YDF machine-learning model:

Number of columns by type:
NUMERICAL: 9 (60%)
CATEGORICAL: 6 (40%)

Columns:
NUMERICAL: 9 (60%)
0: "Probability of Failure" NUMERICAL mean:0.0874883 min:0.0027 max:0.19 sd:0.0290562 dtype:DTYPE_FLOAT64
5: "Height (m)" NUMERICAL mean:17.6929 min:0 max:278.646 sd:21.163 dtype:DTYPE_FLOAT64
6: "Length (km)" NUMERICAL mean:0.424202 min:0 max:14 sd:0.77955 dtype:DTYPE_FLOAT64
7: "Volume (m3)" NUMERICAL mean:377956 min:0 max:1.10551e+08 sd:3.2803e+06 dtype:DTYPE_FLOAT64
8: "Year Completed" NUMERICAL mean:1944.99 min:1850 max:2022 sd:32.8183 dtype:DTYPE_FLOAT64
9: "Surface (km2)" NUMERICAL mean:4.49367 min:0 max:3143.66 sd:57.5464 dtype:DTYPE_FLOAT64
10: "Drainage (km2)" NUMERICAL mean:986.348 min:0 max:919056 sd:16024.1 dtype:DTYPE_FLOAT64
12: "Inspection Frequency" NUMERICAL mean:2.6448 min:0 max:10 sd:2.37541 dtype:DTYPE_FLOAT64
13: "Distance to Nearest City (km)" NUMERICAL mean:16.7191 min:0 max:231.6 sd:21.4028 dtype:DTYPE_FLOAT64

CATEGORICAL: 6 (40%)
1: "Region" CATEGORICAL has-dict vocab-size:2 zero-ood-items most-frequent:"Flumevale" 3522 (100%) dtype:DTYPE_BYTES
2: "Regulated Dam" CATEGORICAL has-dict vocab-size:3 zero-ood-items most-frequent:"Yes" 3257 (92.4759%) dtype:DTYPE_BYTES
3: "Primary Purpose" CATEGORICAL has-dict vocab-size:12 zero-ood-items most-frequent:"Water Supply" 1025 (29.1028%) dtype:DTYPE_BYTES

4: "Primary Type" CATEGORICAL has-dict vocab-size:12 num-oods:3 (0.0851789%) most-frequent:"Earth" 3074 (87.28%) dtype:DTYPE_BYTES
11: "Spillway" CATEGORICAL has-dict vocab-size:4 zero-ood-items most-frequent:"Missing" 1792 (50.8802%) dtype:DTYPE_BYTES
14: "Assessment" CATEGORICAL has-dict vocab-size:7 zero-ood-items most-frequent:"Satisfactory" 1850 (52.527%) dtype:DTYPE_BYTES

Sample of the tree of the tree built by YDF:

Tree #1 of 50:

```
"Inspection Frequency">=5.5 [s:0.00031397 n:3186 np:854 miss:0] ; pred:-2.35608e-10
    ├──(pos)── "Assessment" is in [BITMAP] {<OOD>, Fair, Not Rated, Not Available, Unsatisfactory, Poor} [s:7.90974e-05 n:854 np:643 miss:1] ; pred:-0.00292806
    |   ├──(pos)── "Assessment" is in [BITMAP] {<OOD>, Satisfactory, Unsatisfactory, Poor} [s:4.7757e-05 n:643 np:41 miss:1] ; pred:-0.00241859
    |   |   ├──(pos)── "Height (m)">=9.9615 [s:1.68793e-05 n:41 np:10 miss:1] ; pred:0.000229452
    |   |   |   ├──(pos)── "Distance to Nearest City (km)">=17.37 [s:3.364e-05 n:10 np:5 miss:0] ; pred:-0.000493914
    |   |   |   |   ├──(pos)── pred:-0.00107391
    |   |   |   |   └──(neg)── pred:8.60864e-05
    |   |   |   └──(neg)── "Primary Purpose" is in [BITMAP] {Irrigation, Flood Risk Reduction, Missing} [s:7.85359e-06 n:31 np:25 miss:0] ; pred:0.000462796
    |   |   |       ├──(pos)── pred:0.000600086
    |   |   |       └──(neg)── pred:-0.000109247
    |   |   └──(neg)── "Inspection Frequency">=8.5 [s:1.77675e-05 n:602 np:45 miss:0] ; pred:-0.00259894
    |   |       ├──(pos)── "Volume (m3)">=3040.9 [s:4.12232e-05 n:45 np:30 miss:1] ; pred:-0.00408191
    |   |       |   ├──(pos)── pred:-0.00362791
    |   |       |   └──(neg)── pred:-0.00498991
    |   |       └──(neg)── "Assessment" is in [BITMAP] {<OOD>, Satisfactory, Not Rated, Not Available, Unsatisfactory, Poor} [s:1.98747e-05 n:557 np:356 miss:1] ; pred:-0.00247913
    |   |           ├──(pos)── pred:-0.00214414
    |   |           └──(neg)── pred:-0.00307243
    |   └──(neg)── "Length (km)">=0.5655 [s:2.10222e-06 n:211 np:21 miss:0] ; pred:-0.00448061
    |       ├──(pos)── "Spillway" is in [BITMAP] {<OOD>, Uncontrolled, Controlled} [s:2.89887e-05 n:21 np:14 miss:1] ; pred:-0.00404449
```

```
      |            |        ├─(pos)─ "Drainage (km2)">=3.99494 [s:5.97168e-06 n:14 np:5 miss:1] ;
pred:-0.00366377
      |            |        |        ├─(pos)─ pred:-0.00333591
      |            |        |        └─(neg)─ pred:-0.00384591
      |            |        └─(neg)─ pred:-0.00480591
      |            └─(neg)─ "Volume (m3)">=22742 [s:2.95476e-06 n:190 np:76 miss:1] ;
pred:-0.00452881
      |                     ├─(pos)─ "Volume (m3)">=24655 [s:8.13557e-06 n:76 np:68 miss:1] ;
pred:-0.00473933
      |                     |        ├─(pos)─ pred:-0.0046415
      |                     |        └─(neg)─ pred:-0.00557091
      |                     └─(neg)─ "Distance to Nearest City (km)">=4.795 [s:3.53561e-06 n:114
np:90 miss:1] ; pred:-0.00438846
      |                              ├─(pos)─ pred:-0.00429136
      |                              └─(neg)─ pred:-0.00475258
      └─(neg)─ "Inspection Frequency">=0.75 [s:0.000104824 n:2332 np:1877 miss:1] ;
pred:0.00107228
             ├─(pos)─ "Assessment" is in [BITMAP] {Fair, Not Rated, Not Available,
Unsatisfactory, Poor} [s:6.27985e-05 n:1877 np:705 miss:0] ; pred:0.00157637
             |      ├─(pos)─ "Inspection Frequency">=2.5 [s:0.000173619 n:705 np:210 miss:1] ;
pred:0.00259811
             |      |        ├─(pos)─ "Primary Type" is in [BITMAP] {<OOD>, Earth, Concrete,
Rockfill, Arch, Buttress, Other, Multi-Arch, Masonry, Roller-Compacted Concrete}
[s:6.59684e-05 n:210 np:185 miss:1] ; pred:0.000575134
             |      |        |        ├─(pos)─ pred:0.000873708
             |      |        |        └─(neg)─ pred:-0.00163431
             |      |        └─(neg)─ "Inspection Frequency">=1.5 [s:0.000123326 n:495 np:114
miss:1] ; pred:0.00345635
             |      |                 ├─(pos)─ pred:0.00548654
             |      |                 └─(neg)─ pred:0.00284889
             |      └─(neg)─ "Inspection Frequency">=2.5 [s:4.60266e-05 n:1172 np:142 miss:1] ;
pred:0.000961749
             |               ├─(pos)─ "Primary Purpose" is in [BITMAP] {<OOD>, Flood Risk
Reduction, Recreation, Other, Fish and Wildlife Pond, Fire Protection, Stock, Or Small Fish
Pond, Debris Control, Missing, Tailings} [s:0.000116198 n:142 np:60 miss:1] ;
pred:-0.000865421
             |               |        ├─(pos)─ pred:0.000394753
             |               |        └─(neg)─ pred:-0.0017875
             |               └─(neg)─ "Inspection Frequency">=1.5 [s:7.10385e-05 n:1030 np:130
miss:1] ; pred:0.00121365
```

```
    |                    ├─(pos)─ pred:0.00343132
    |                    └─(neg)─ pred:0.00089332
    └─(neg)─ "Assessment" is in [BITMAP] {<OOD>, Fair, Not Rated, Not Available, Unsatisfactory, Poor} [s:0.000125435 n:455 np:150 miss:1] ; pred:-0.00100721
        ├─(pos)─ "Assessment" is in [BITMAP] {Not Available, Unsatisfactory} [s:0.000130302 n:150 np:20 miss:0] ; pred:0.00058982
        |   ├─(pos)─ "Primary Purpose" is in [BITMAP] {Fire Protection, Stock, Or Small Fish Pond, Missing} [s:0.000149974 n:20 np:6 miss:0] ; pred:0.00350009
        |   |   ├─(pos)─ pred:0.00537075
        |   |   └─(neg)─ pred:0.00269837
        |   └─(neg)─ "Assessment" is in [BITMAP] {<OOD>, Satisfactory, Not Rated, Not Available, Unsatisfactory, Poor} [s:1.59922e-05 n:130 np:73 miss:1] ; pred:0.000142086
        |       ├─(pos)─ pred:0.000495456
        |       └─(neg)─ pred:-0.000310475
        └─(neg)─ "Primary Purpose" is in [BITMAP] {<OOD>, Water Supply, Irrigation, Flood Risk Reduction, Hydroelectric, Fish and Wildlife Pond, Tailings} [s:3.0658e-06 n:305 np:229 miss:1] ; pred:-0.00179263
            ├─(pos)─ "Height (m)">=19.0865 [s:3.26218e-06 n:229 np:19 miss:0] ; pred:-0.00169177
            |   ├─(pos)─ pred:-0.00229223
            |   └─(neg)─ pred:-0.00163744
            └─(neg)─ "Surface (km2)">=0.180255 [s:6.6646e-06 n:76 np:29 miss:1] ; pred:-0.00209657
                ├─(pos)─ pred:-0.00242522
                └─(neg)─ pred:-0.00189379
Train model on 3522 examples
Model trained in 0:00:00.205943
```

YDF-model generated description regarding the importance of each variable, sorted by their inverse mean depth from the root.

Variable importances measure the importance of an input feature for a model. Here are our variable importances:

INV_MEAN_MIN_DEPTH

1. "Inspection Frequency" 0.475367 ################
2. "Assessment" 0.302383 ######
3. "Distance to Nearest City (km)" 0.194697
4. "Surface (km2)" 0.193772
5. "Primary Type" 0.193499
6. "Length (km)" 0.193060
7. "Primary Purpose" 0.191314
8. "Drainage (km2)" 0.191283
9. "Height (m)" 0.191071
10. "Volume (m3)" 0.186913
11. "Year Completed" 0.181479
12. "Spillway" 0.176465
13. "Regulated Dam" 0.176164

Those variable importances are computed during training. More, and possibly more informative, variable importances are available when analyzing a model on a test dataset.

12. Appendix D – Additional Sensitivity Analysis

Region	Inspection Frequency	Threshold percent	Original Threshold	New Threshold	Change in Threshold	Original Expected Payout	New Expected Payout	Change in Payout
	0	0.9501	212000.38	212160.72	160.34	191945.27	192073.42	128.15
	1	0.9501	212000.38	212163.38	163.00	191945.27	192076.10	130.83
	2	0.9501	212000.38	212193.25	192.87	191945.27	192106.83	161.56
	3	0.9503	212000.38	209598.16	-2402.22	191945.27	189440.28	-2504.99
	4	0.9508	212000.38	202757.87	-9242.51	191945.27	182472.63	-9472.64
	5	0.9508	212000.38	200192.04	-11808.34	191945.27	179883.40	-12061.87
	6	0.9509	212000.38	198133.74	-13866.64	191945.27	177809.75	-14135.52
Flume vale	**7**	0.9509	212000.38	198133.74	-13866.64	191945.27	177809.75	-14135.52
	8	0.9509	212000.38	198133.74	-13866.64	191945.27	177809.75	-14135.52
	9	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	10	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	11	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	12	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	13	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35

	14	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	15	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	16	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	17	0.9510	212000.38	193820.05	-18180.33	191945.27	173454.92	-18490.35
	0	0.9502	300498.72	300013.90	-484.81	280293.45	279754.15	-539.30
	1	0.9506	300498.72	288754.05	-11744.67	280293.45	268383.45	-11910.00
	2	0.9510	300498.72	274533.02	-25965.70	280293.45	254037.29	-26256.16
	3	0.9510	300498.72	272594.63	-27904.09	280293.45	252076.73	-28216.72
	4	0.9521	300498.72	241884.29	-58614.42	280293.45	221022.61	-59270.84
	5	0.9526	300498.72	227640.33	-72858.38	280293.45	206617.27	-73676.18
	6	0.9530	300498.72	214549.08	-85949.63	280293.45	193405.43	-86888.02
Lyndrassia	**7**	0.9530	300498.72	214549.08	-85949.63	280293.45	193405.43	-86888.02
	8	0.9532	300498.72	206078.87	-94419.85	280293.45	184862.98	-95430.47
	9	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	10	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	11	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	12	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28

	13	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	14	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	15	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	16	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	17	0.9540	300498.72	162103.71	-138395.01	280293.45	140636.18	-139657.28
	0	0.9501	351907.44	351891.88	-15.56	326403.70	326341.63	-62.06
	1	0.9501	351907.44	351761.97	-145.47	326403.70	326210.66	-193.04
	2	0.9501	351907.44	350697.12	-1210.32	326403.70	325141.33	-1262.37
	3	0.9503	351907.44	347765.94	-4141.50	326403.70	322151.28	-4252.42
	4	0.9505	351907.44	343943.97	-7963.47	326403.70	318268.89	-8134.80
	5	0.9518	351907.44	312878.50	-39028.94	326403.70	286671.04	-39732.66
	6	0.9523	351907.44	295528.07	-56379.37	326403.70	269145.63	-57258.07
Navaldia	**7**	0.9524	351907.44	288609.84	-63297.60	326403.70	262168.15	-64235.55
	8	0.9521	351907.44	300315.44	-51592.00	326403.70	273979.68	-52424.02
	9	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92
	10	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92
	11	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92

	12	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92
	13	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92
	14	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92
	15	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92
	16	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92
	17	0.9528	351907.44	275220.35	-76687.09	326403.70	248626.78	-77776.92

Figure 19: Comparative Threshold and Payout Adjustment across Inspection Frequency

Location	**Initial Threshold Percent**	**Final Threshold Percent**	**Change in Threshold Percent**	**Initial Expected Payout**	**Final Expected Payout**	**Change in Expected Payout**	**% Change in Expected Payout**	**Elasticity**
Flumevale	0.950109	0.951034	0.000925	192,073.42	173,454.92	-18618.5	-9.69	-99.5
Lyndrassia	0.950183	0.953968	0.00378	279,754.15	140,636.18	-139117.9	-49.73	-124.9
Navaldia	0.950124	0.952774	0.00265	326,341.63	248,626.78	-77714.85	-23.81	-85.3

Figure 20: Elasticity of Expected Payouts to Threshold Percent across Regions

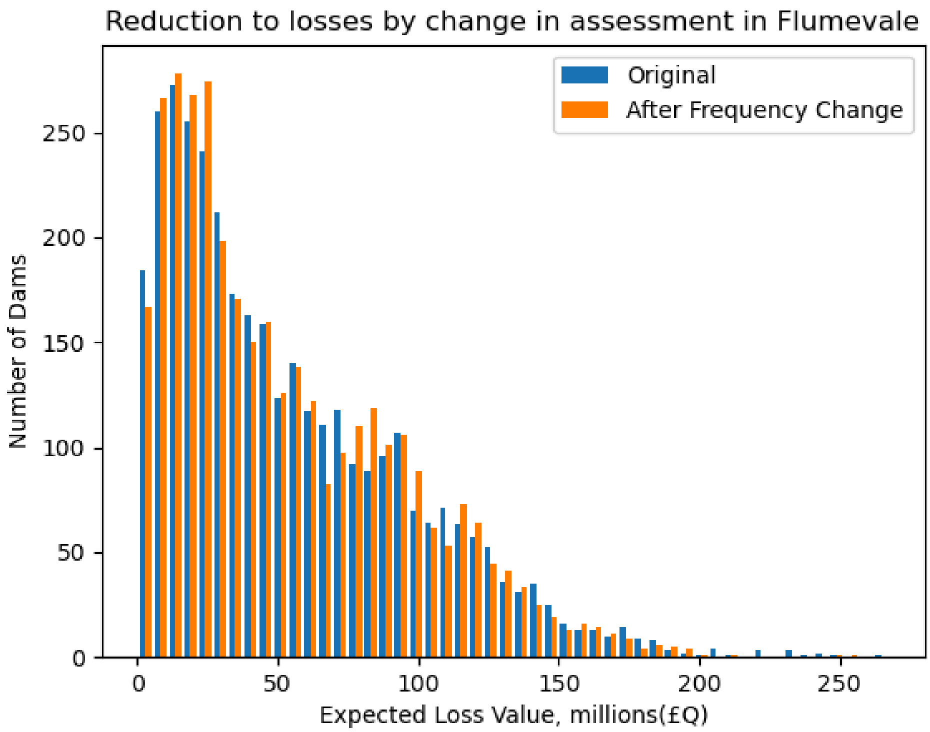


Figure 21: Assessment Adjusted Expected Loss in Flumevale with an Fair Assessment Rating

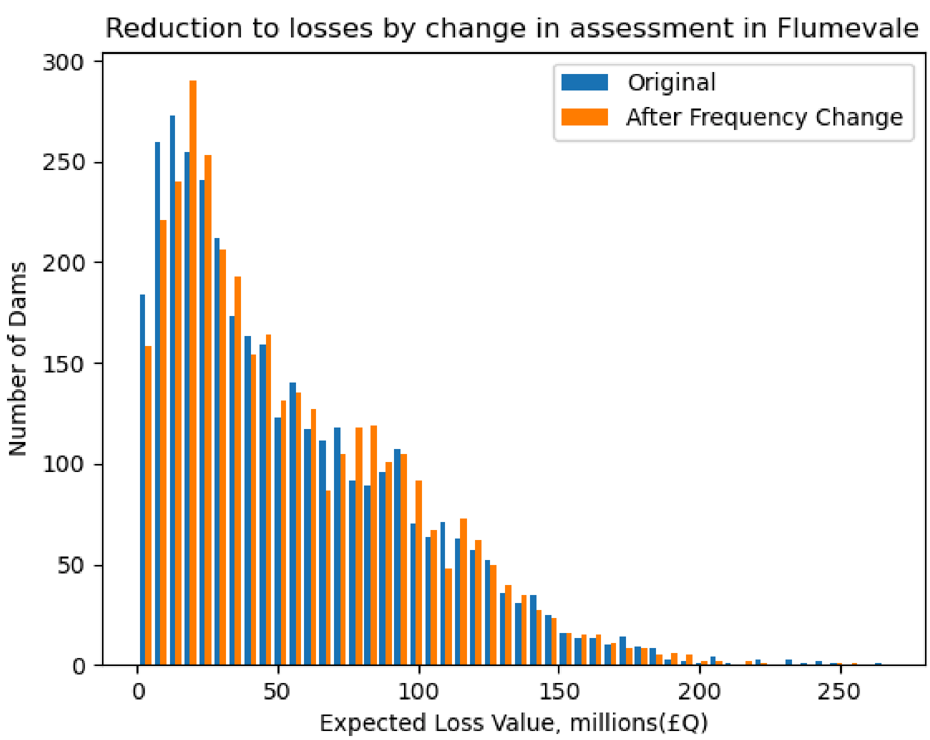


Figure 22: Assessment Adjusted Expected Loss in Flumevale with a Poor Assessment Rating

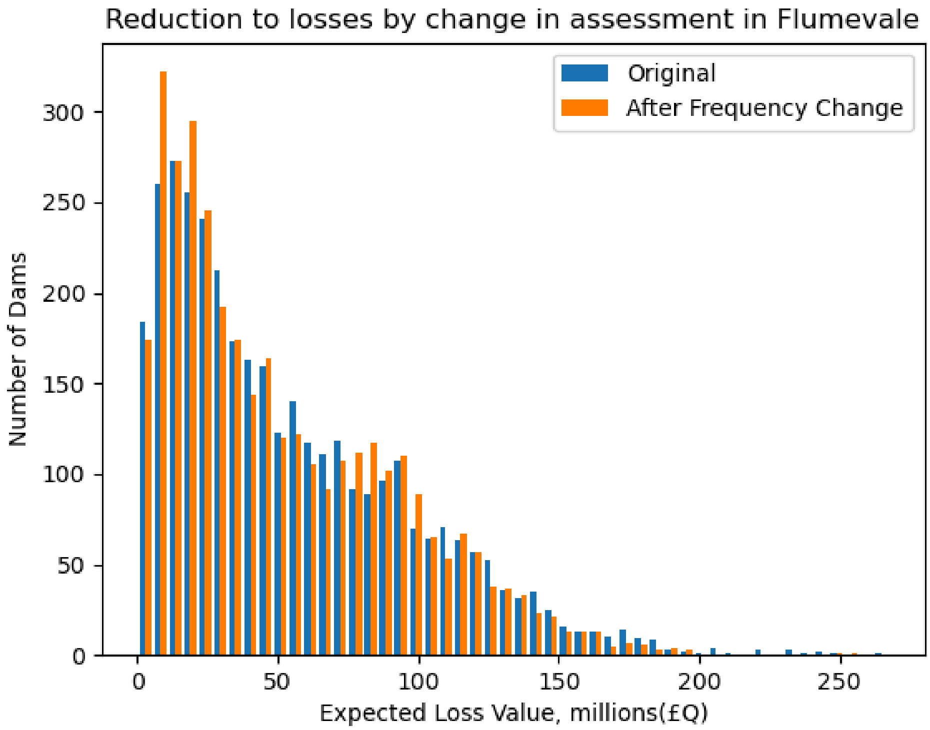


Figure 23: Assessment Adjusted Expected Loss in Flumevale with a Satisfactory Assessment Rating

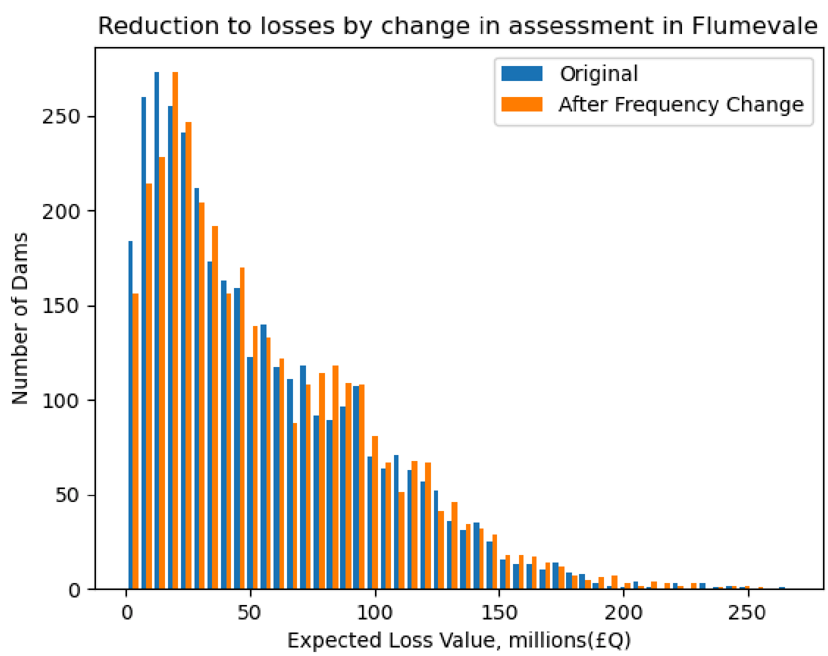


Figure 24: Assessment Adjusted Expected Loss in Flumevale with an Unsatisfactory Assessment Rating

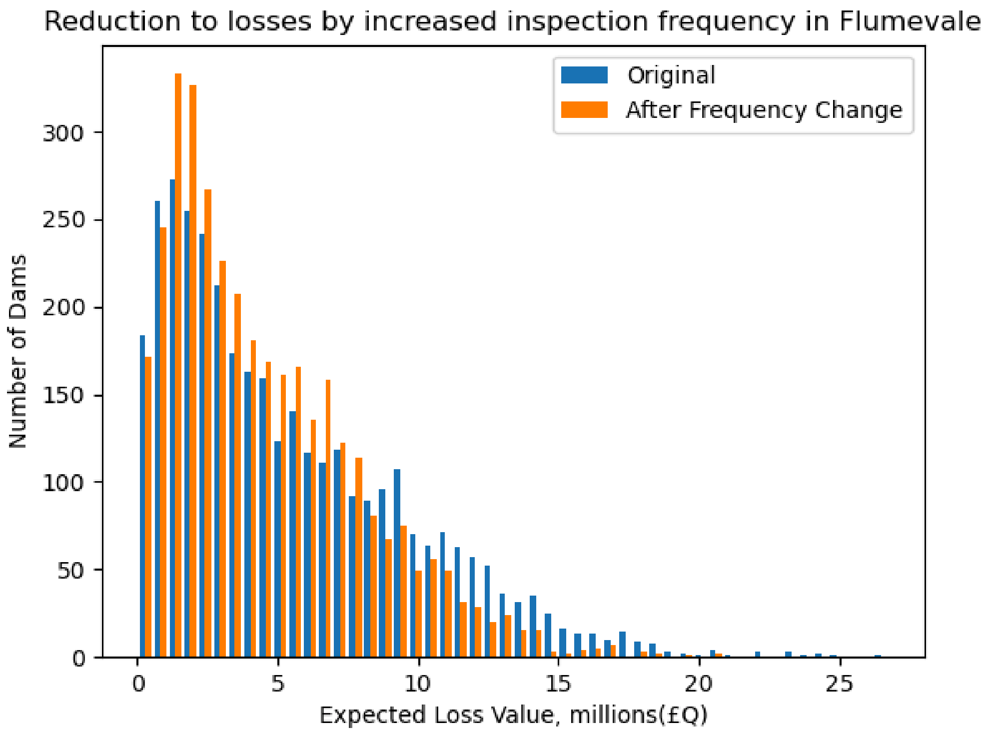


Figure 25: Adjusted Expected Loss Due to Minimum Inspection Frequency of 3 in Flumevale

Findings are the following:

- Flumevale: The expected payout decreases by 9.69% as the threshold percent rises from 0.950109 to 0.951034. An elasticity of -99.5 means a 1% increase in threshold percent reduces the payout by about 99.5%, indicating high sensitivity.
- Lyndrassia: Shows the largest drop at 49.73%, with an elasticity of -124.9, suggesting extreme sensitivity—small parameter changes drastically cut payouts, possibly due to a significant threshold reduction (-138,395).
- Navaldia: A 23.81% payout reduction with an elasticity of -85.3, less sensitive than Lyndrassia but still significant.

The decreasing payouts despite a rising threshold percent (and falling thresholds) suggest the model adjusts risk downward over scenarios, possibly reflecting reduced event severity or probability. Lyndrassia's heightened sensitivity implies it's more vulnerable to parameter tweaks, requiring careful calibration in risk management. This table quantifies these shifts, aiding in assessing risk exposure across locations.

13. Appendix E – Additional Risks

Risk	Description	Mitigation Strategy
Market Monopolization	Large insurers could dominate the market, inflating premiums and reducing efficiency, particularly if smaller competitors are forced out.	Regulate market entry and pricing to promote competition. Offer temporary claim support to smaller insurers during catastrophic events, preventing market consolidation and ensuring affordable premiums.
Poor Inspection Quality	Inadequate inspections may fail to detect risks, increasing the probability of dam failures and subsequent flood-related claims.	Standardize inspection protocols with industry expertise to ensure thorough, consistent evaluations. Enforce compliance by imposing higher claim thresholds or penalties on reinsurers failing to meet inspection standards.
Insolvency Risk for Small Insurers	Small insurers may collapse under the weight of large-scale claims, destabilizing the insurance market.	Enforce minimum capital reserve requirements for direct insurers and reinsurers to maintain financial stability. Provide temporary government claim support to prevent insolvencies following catastrophic events.

14. Appendix F – Additional Assumptions

Metric	Description	Rationale
Attachment/Detachment Points for Reinsurance	Reinsurance attachment is set at the 80th percentile and detachment at the 95th percentile of the expected loss distribution.	This structure follows the current industry standard, which balances risk-sharing between direct insurers and reinsurers. It limits reinsurer exposure to high-frequency, low-severity losses while ensuring

		coverage for catastrophic events.
Standardized Inspections	Uniform inspection protocols apply across all regions, with adjustments for specific risks such as climate and floodplain exposure. Inspection frequency does not impact quality.	Standardized inspections mitigate dam failure risk by enabling early detection of maintenance issues. This model assumes a negative correlation between inspection frequency and failure probability.
Assumption of average salary per person in each region	Assumption in which the average salary is equal to the GDP per capita per region.	This average salary helps to give a general view of the burden in tax per person of our program. In order to measure the affordability of our model.

15. Appendix G – Bibliography

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